Hyperspectral imaging requires reinventing multispectral concepts

Chein-I Chang

By incorporating information from hundreds of contiguous spectral bands, hyperspectral imaging provides a fuller picture of an unknown target than previously possible.

Hyperspectral imaging (HSI) uses remote sensors to capture and process spectral information over a range of wavelengths, generally in the visible to near-infrared part of the electromagnetic spectrum. HSI uses hundreds of contiguous spectral bands, which yield an image cube, rather than the tens of discrete spectral bands used in multispectral imagery. As a result, HSI has expanded the capability of multispectral imaging in numerous applications in agriculture, ecology, geology, environmental monitoring, military intelligence, law enforcement, and chemical and biological defense. Many unknown substances that cannot be resolved by multispectral imagery can now be uncovered using HSI sensors. However, this benefit comes at a price, namely, the knowledge needed to effectively use the spectral information resulting from these hundreds of bands to perform various tasks in data exploitation. Thus, various concepts must be reinvented from a hyperspectral imagery viewpoint. One that has proved to be promising is the ‘pigeonhole’ principle.

The pigeonhole principle states that if there are \( p \) pigeons flying into \( L \) pigeonholes with \( p > L \), there exists at least one pigeonhole that must accommodate more than one pigeon. Using this principle, we can interpret a pigeonhole as a spectral band and a pigeon as a target such that a spectral band (a pigeonhole) can be used to accommodate a distinct target (a pigeon). Since \( L \) spectral bands are available from HSI, according to the pigeonhole principle we can use these \( L \) spectrally distinct bands to accommodate \( L \) spectrally distinct targets using one band to detect and classify each particular target.

To make the pigeonhole principle work for HSI, four issues need to be addressed. First, the number of bands, \( L \), cannot be smaller than the number of target sources, \( p \), that is, \( p \leq L \). HSI generally satisfies this requirement. Second, after one band is used to accommodate a target source, it cannot be used again. The orthogonal subspace projection (OSP) was developed to ensure that bands are not reused. Third, since \( p \leq L \), the next issue is to determine \( p \) using virtual dimensionality (VD), which was designed to estimate how many spectrally distinct targets are available in the data. Finally, once \( p \) is determined, a follow-up issue is to find \( p \) target sources. This can be accomplished by designing unsupervised target-finding algorithms.

Various applications of HSI have been investigated recently. As a peek at this cutting-edge technique, the real image shown in Figure 1 is used to demonstrate three major applications, namely, endmember extraction, subpixel target detection, and mixed pixel classification.
Figure 2. The endmembers, marked by open circles, have been extracted by (left) the pixel purity index (PPI) method and (right) the N-finder algorithm (N-FINDR).

An endmember is an idealized, pure signature that represents a spectral class. From the ground truth in Figure 1(b), 14 panel pixels, \( P_{11}, P_{21}, P_{22}, P_{31}, P_{32}, P_{41}, P_{42}, P_{51}, P_{52}, P_{12}, P_{22}, P_{32}, P_{42}, \) and \( P_{52} \) are considered to be pure pixels representing five distinct pure signatures. Figure 2 shows the endmembers extracted using two popular endmember extraction algorithms. The first is the pixel purity index (PPI), which uses 200 skewers. The second is the N-finder algorithm (N-FINDR), which reduces the dimensionality of the original data to nine components by maximum noise fraction (MNF) transformation. The VD estimates using the number of MNF components.

A subpixel target is an object whose size is smaller than a pixel resolution and generally cannot be visualized by inspection. The five panel pixels in the third column of Figure 1(b), \( P_{13}, P_{23}, P_{33}, P_{43}, \) and \( P_{53} \), can be considered subpixel targets. Using each of the five panel signatures, \( P_1, P_2, P_3, P_4, \) and \( P_5 \) in Figure 1(c) as a desired target signature, Figure 3 shows the results for each panel signature produced by constrained energy minimization (CEM). The five subpixel targets are successfully detected by CEM.

A mixed pixel is an admixture resulting from a combination of substances resident in a pixel. The four background signatures, \( P_B, P_G, P_T, P_R \), obtained from Figure 1(d) are mixed pixels. These are further combined with the five panel signatures, \( P_1, P_2, P_3, P_4, \) and \( P_5 \), to form a linear mixture model for spectral unmixing. Figure 4 shows the mixed pixel classification results produced by three spectral unmixing methods, least squares orthogonal subspace projection (LSOSP), non-negativity abundance constrained least squares (NCLS), and fully abundance constrained least squares (FCLS). By visual assessment, NCLS seems to be the best method. All 19 panel pixels are correctly classified.

HSI has great potential to expand and improve remote sensing to reveal many more substances for data exploration and analysis. However, the advantages of HSI are traded for a lack of knowledge that cannot be obtained using prior information. This leads to several challenges, including how to produce unsupervised knowledge directly from the data, how to effectively use the available information, and how to design algorithms to find targets of interest without appealing to prior knowledge. Many research efforts have been directed toward addressing these issues. Because of the great variety of applications for HSI, future work also aims to improve endmember extraction, anomaly detection, subpixel target detection, mixed pixel analysis (including discrimination, classification, quantification, and identification), unsupervised target analysis, and data compression.

Continued on next page
Author Information

Chein-I Chang
Remote Sensing Signal and Image Processing Laboratory
Department of Computer Science and Electrical Engineering
University of Maryland, Baltimore County
Baltimore, MD

Environmental Restoration and Disaster Reduction
Research Center
Department of Electrical Engineering
National Chung Hsing University
Taichung, Taiwan
http://www.umbc.edu/rssipl

Chein-I Chang is a professor at the University of Maryland, Baltimore County, and received his PhD in electrical engineering from the University of Maryland, College Park. He has published 100 journal articles, authored a book, Hyperspectral Imaging, edited two books, Recent Advances in Hyperspectral Signal and Image Processing and Hyperspectral Data Exploitation: Theory and Applications, and co-edited a book, High Performance Computing in Remote Sensing. He is a SPIE Fellow and currently on the editorial board of the Journal of High Speed Networks, Recent Patents on Mechanical Engineering, and Open Remote Sensing Journal. He is also a member of the SPIE program committees for Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery, the International Symposium on Optical Science and Technology, and the Conference on Imaging Spectrometry.

References